TECHNISCHE UNIVERSITÄT KAISERSLAUTERN

Exercise 5 - 2D Image Processing

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Optical Flow

1. ...

2.
   - brightness consistency: for a fixed light source or even a light source that moves only slowly, it should be possible to track bubbles. On the other hand, if the light source moves rather fast, it is not easily possible. (this is directly connected to "temporal persistence")
   - spacial coherence: since bubbles do not vanish while being in the liquid, points should move similarly with respect to their neighbors.

3. ...

4.
   - Consider a transparent plane with some colored dots on it. Let the background either be very far away or unicolored. Moving the mentioned plane in any direction yields the neighbors of the dots moving differently, so violating neighbor consistency property.
   - Consider a car that drives at night and enters a street light during the observed time period. Then the brightness consistancy does not hold anymore.
   - Consider a car driving on a motorway with high velocity. If the camera's shutter frequency is not fast enough the resulting motion of the car is too large and the Lucas-Kanade optical flow fails.

5. ...

Bayes Filter

1. We use a distribution function to estimate the probability where an object might be located after a timestep. Using additional sensor data, we are able to compute another probability region where the object should be. Using both steps together, we are able to correct the measurements and therefore are more likely to get a robust estimation of the current location of the object. The main idea of doing this iteratively, is to prevent divergence of the model, due to insuffiencient measurements.

2. The state contains all information that we want to know about the system. Color can also be seen as a state, as shown in the lecture on July 11.

3. $$L(x_t) = \eta p(z_t|x_t) \int p(x_t|x_{t-1}, u_t) L(x_{t-1}) dx_{t-1}$$

   - $p(z_t|x_t)$: probability of the new measurement z_t given the previous state x_{t-1}
   - $p(x_t|x_{t-1}, u_t)$: probability of the new state x_t given both, previous state x_{t-1} and previous control data u_t
   - $L(x_t)$: estimated location at time t

Kalman Filter

1. Markov assumption states that the currently observed state x_t depends only on the previous state x_{t-1}. The assumption for example holds in case of the random walk in $\mathbb{R}^d$. An example where the assumption is violated is Fibonacci's sequence

   $$x_t = x_{t-1} + x_{t-2},$$

   where each state depends on the previous two states.

2. ...